AUGMENTATION TECHNIQUE FOR ARTIFICIAL PHASE-CONTRAST MICROSCOPY IMAGES GENERATION FOR THE TRAINING OF DEEP LEARNING ALGORITHMS

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Abstract: Phase contrast segmentation is crucial for various biological tasks such us quantitative, comparative or single cell level analysis. The popularity of image segmentation using deep learning strategies has been transferred into the field of microscopy imaging as well. Since the huge amount of training data is usually required, the annotation is time-consuming and lengthy. This paper introduces the method and augmentation techniques for artificial phase-contrast images generation aiming at the training of deep learning algorithms.

Keywords: deep learning, phase-contrast, cell segmentation, data augmentation, artificial data generation

1 INTRODUCTION

Deep learning algorithms achieved state-of-the-art performance in many technical and scientific fields. The trend of deep learning era may seem still rising. However, some of the limitations occur more often with the application attempts in the new scientific fields with the lack of reliable ground truth data. Deep learning algorithms provide reliable results as far as the training data set is well controlled, equally distributed and furthermore representative.

Phase contrast imaging produces high-contrast images of transparent [1]. Thus, the method is suitable for cell visualization, detection and tracking or analysis. Deep learning algorithms seem suitable for cell detection and semantic segmentation. However, the problem arises with the lack of the training and validation images in the sufficient amount required for deep learning procedures.

This paper introduces the method for artificial phase contrast real-like image generation using a small number of annotated input cells. The intention is to use these images for the deep learning model training. The efficiency of the results is demonstrated on the Mask-RCNN [3] training using only artificial data, and the model inference is performed and evaluated on the artificial and also real images.

2 METHODS

It is essential to keep not only the statistical distribution, of the artificial image, as close as possible to the real one. The background distribution and its possible artefacts should represent the real background to prevent high false-positivity ratio caused by these artefacts. Thus, the artificial image synthesis is divided into two main parts, where the first one is background generation and the second the cell augmentation and to-real-like transformation.

2.1 BACKGROUND GENERATION

The process of background generation takes the real image as an input. Previous background analysis provides estimations of the background mean value μ and maximum possible deviation T. Image pixel values higher than the maximum possible background deviation are suppressed by adaptive amplitude suppression. Thus, the background artefacts, beneath the threshold value T, stay untouched, whereas higher values are suppressed. The formula (1) is iteratively applied on the image $X(x,y)$ until all pixel values do not fulfil the threshold criterion. The suppression iterates by the i variable.

$$X_{i+1}(x,y) = \begin{cases} X_i(x,y) & , \text{ if } |X_i(x,y) - \mu| < t \\ 0.5 * (X_{i+1}(x,y) - \mu) + \mu & , \text{ otherwise} \end{cases} \quad (1)$$

The original input image and the after-suppression artificial background is shown in figure 1 together with the cross-section through the example images (a) and (b). The background for the synthetic image is obtained as a random crop from the whole size image.

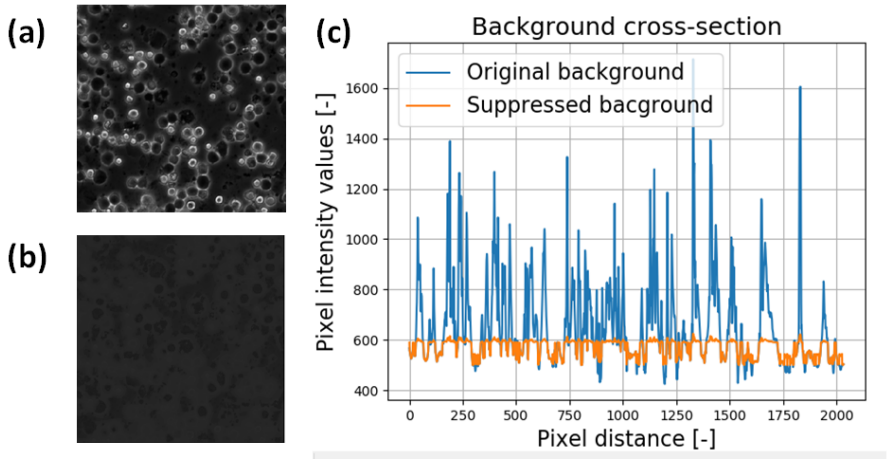

Figure 1: (a) original image with cells. (b) the after-suppression image which is used as a background for an artificial image. (c) Cross-section through the center of the image before and after adaptive amplitude suppression.

2.2 ARTIFICIAL CELL GENERATION

The typical hallow artefact is specific for the cells visualization using phase-contrast microscopy. The hallow artefact is characterized by the intensity increase around the cell membrane and fading with the distance from the cell. The overall effect appears as a non-homogeneous ring around a cell. Three basic cell types (a-c) of the used phase-contrast images are shown in figure 2 in section (1). There is a need for manual annotation of the initial data set, which is used in following the procedure. The higher number of annotated cell masks increases the robustness of the synthetic images and their effect on the training. The segmented cells are shown in the section (2) of figure 2.

The process of artificial hallow generation is divided into several parts. At first, the binary segmentation mask is dilated (3 pixels), so the brightest part of original hallow may be cropped from the original image. The cropped cell (using extended mask) is pasted into the new image, where the cell (original segmentation mask, not extended) itself is replaced with the maximum pixel value from the area of dilated mask. So, there is a tight hallow-ring filled with a maximum brightness value. Then, the set of blurring filters is applied. The original hallow-ring filled with maximum cell value is pasted onto the same position before each filtration. Thus, the morphological details around the cell are kept.

In the final part, only the cell (initial mask) is placed into the image with the artificially created hallow effect. The result is shown in the section (3) in figure 2.

Random rotation and perspective transformation forego the to-real-like transformation process. Thus, the higher variability in the image is achieved. The final step is the random placement of a randomly chosen and augmented cell into the synthetic image.

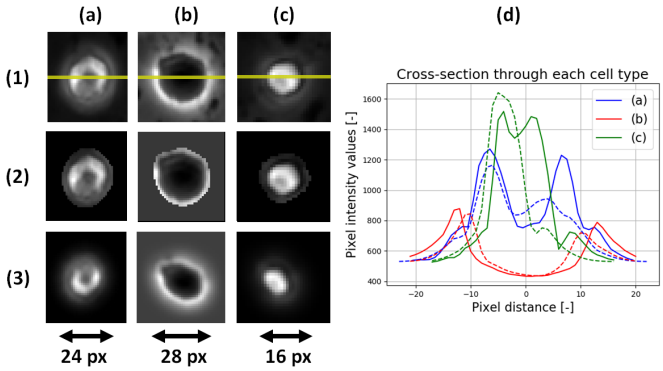

Figure 2: The left part shows three optically different types of cells (1) (a-c) appearing in the inspected phase contrast images. (2) Cells cropped by the annotated mask. (3) Randomly transformed cells with artificially generated hallow using the method described in this paper. (c) Cross-section through the original cells (1) and synthetic cells (3). The yellow line displays the crop in section (1). The full line corresponds to the section (1) and dashed line to the section (3)

3 RESULTS

The strategy for the synthetic cell images generation was proposed and implemented. 1000 training and 50 testing images were generated. The Mask-RCNN were trained with this data following results were achieved. The precision, recall and F1 score for real images 99.59%, 92.07%, 95.68%. The same attributes for the artificial images 98.9%, 79.8%, 89.21%. The ground truth is images evaluated by an expert biologist with an overall amount of 300 cells. The example of the synthetic image in comparison with the real one is shown in section (a, b) in figure 3.

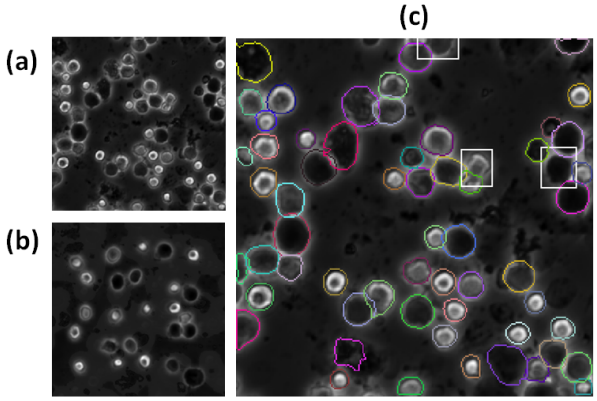

Figure 3: (a) Real phase-contrast image. (b) artificial image. (c) inference on the real data (a) trained on artificial images (b).

4 CONCLUSION

This paper shows the significance of augmentation techniques and artificial data synthesis for cell semantic segmentation using deep learning algorithms. Mask-RCNN model trained only with synthetic data shows the advantage of synthetic data generation. Only less than 40 cells were used for the image synthesis, but the deep model shows satisfactory results nevertheless. Although, the introduction of entirely new cell types or microscopy technique images may cause a drop in performance. On the other hand, the same approach for data generation may be performed. The performance increase for the testing on the real data shows the robustness of the artificial data synthesis. The possible discussion about training setup, algorithm choice and the fine tuning is behind the scope of this paper. The inference and prediction performed on the real data are shown in figure 3 (c).

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